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Research article

On the accuracy of crop production and water requirement calculations: Process-based crop modeling at daily, semi-weekly, and weekly time steps for integrated assessments

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A B S T R A C T

Integrated models are crucial for evaluation of the complex interactions and trade-offs among policy choices and socioeconomic, technical, and environmental processes. The use of process-based crop models as components of integrated models offers the possibility of significantly improving such analyses; however, challenges exist in terms of simulation scales and degree of integration. Therefore, this study evaluates the applicability of coarser-than-daily simulation time steps to simulate long-term crop yields in integrated models, and the impacts of aggregated weather input data on yields for a water-driven crop-process model based on the FAO AquaCrop model. We ran simulations at daily, semi-weekly, and weekly time steps in conjunction with coarser temporal resolution (weekly) weather input data for three crops in four locations over ten years to represent a range of crops and growing environments. Simulation results were compared to a reference case from AquaCrop using daily time step with daily weather data. Model skill for simulating crop biomass and yield and water demands was assessed statistically for each of these four hypothetical farms. Visual representations were also used to compare simulated soil moisture, crop canopy, and actual evapotranspiration values. Weekly climate data led to overestimation of crop biomass and yield regardless of the time step used. High agreements and low bias errors were realized for crop production and water estimates at daily and semi-weekly time steps, whereas weekly simulations showed poorer performance. Longer time steps intensified the impacts of weather input data aggregation, and overestimation became more pronounced with increases in time step length. The findings have important implications for integrated assessments that couple crop models with other socioeconomic, environmental, or hydrologic models, and provide guidance for modelers involved in interdisciplinary agricultural and water resources applications, including policy assessments, evaluation of water and food security, and resource use and efficiency under climate change.

1. Introduction

Agricultural production models have been applied increasingly in integrated, multidisciplinary studies related to climate change assessment and adaptation (Aurbacher et al., 2013; Bassu et al., 2014; Ewert et al., 2015; Lehmann et al., 2013), food security (Godfray et al., 2010; Tubiello and Ewert, 2002), mixed crop-livestock systems (Tendall and Gaillard, 2015; Thornton and Herrero, 2001; Tracy and Zhang, 2008), and agricultural and water policy assessments (Bryan et al., 2011; García-Vila et al., 2009; García-Vila and Fereres, 2012; Therond et al., 2009). See Holzworth et al. (2015) and citations within for a review of further applications. This breadth of applications represents,

- Recognition of the interconnectedness of systems that were typically treated independently in the past (Jones et al., 2017a; Reidsma et al., 2018), and increased effort to identify and solve complex, integrated problems;
- Advances in the state of modeling natural systems (Faramarzi et al., 2017), human behavior (Binks et al., 2016; Turner et al., 2016), and the connections between them (Davies and Simonovic, 2011; Inam et al., 2017; Kotir et al., 2017);
- Increased understanding of climate change and its effects on ecosystems and human well-being (Faramarzi et al., 2013; Gosling and Arnell, 2016; Myers et al., 2017; Pecl et al., 2017); and,
- Increased capabilities of computer systems (Capalbo et al., 2017; Ferrández-Villena and Ruiz-Canales, 2017; Lundström and Lindblom, 2018).

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Integrated models are crucial for evaluating, and potentially understanding, complex interactions and trade-offs among policy choices and socioeconomic, technical, and environmental processes (Kelly et al., 2013); further, such models typically require long simulation periods – from multi-year to multi-decadal – to permit long-term impacts to become evident and then to accumulate. Integrated agricultural models use crop models as the core component to predict crop responses to varying climatic and agronomic conditions. Such crop models range in complexity from simple empirical relationships to highly-complex, process-based growth models. They can be categorized as statistical crop models – which predict crop yield by fitting a function to historical observations over multiple years – or mechanistic crop models, which are process-based and use functions that describe the various processes of crop growth with a high level of detail.

Statistical crop models (e.g. production functions) can be used as inputs to broader spatial and/or longer temporal scale studies, where they can be coupled relatively easily with other economic or hydrologic models (Cai et al., 2003; Kahil et al., 2016) to provide insights into historical trends of crop yields, for example. However, these “reduced form crop models” (Jones et al., 2017b) are often developed to represent local agronomic and environmental conditions (Bennett et al., 2014; Keating et al., 2002; Prasad et al., 2006) and their development depends on long historical data records of crop yields and climate or water variables (Lobell, 2013; Lobell and Burke, 2010). Thus, they cannot be applied with confidence to extrapolate responses that are outside their estimation domain (Jones et al., 2017b), and cannot capture the effects of increasing atmospheric CO_2 concentrations or long-term changes in temperature on crop yields (Basso et al., 2015).

As an alternative to statistical models, process-based crop models provide an accurate representation of crop-yield responses to weather, soil moisture and nutrient contents, and to agronomic practices. A number of dynamic process-based crop models have been developed, many of which are both widely-used and well-established, including APSIM (Keating et al., 2003); FAO's AquaCrop (Raes et al., 2009; Steduto et al., 2009); CropSyst (Stöckle et al., 2003); DSSAT (Jones et al., 2003); EPIC (Sharpley et al., 1990; Williams, 1990); RZWQM2 (Ahuja et al., 2000); STICS (Brisson et al., 2003, 1998); and WOFOST (Diepen et al., 1989; Supit et al., 1994). Many more models are also available; see Rivington and Koo (2010) and Di Paola et al. (2016) for surveys of existing tools.

Process-based crop models use deterministic functions that describe cause-and-effect relationships between crop yields and external drivers including changes in atmospheric CO_2 concentrations. Therefore, they are typically superior to statistical models, and are the only suitable tools for quantitative assessment of future crop productivity under climate change (Basso et al., 2015; van Bussel et al., 2011). Therefore, their coupling with socioeconomic, environmental, or hydrologic models for integrated assessments is inevitable, despite the fact that such integration is challenging and time consuming, and typically requires skilled modelers and programmers due to differences in the temporal and spatial scales of the models and reliance on legacy modeling approaches that are difficult to integrate (Hamilton et al., 2015; Holzworth et al., 2015; Malard et al., 2017). Further, process-based models often rely on fine-scaled data series that are hard to obtain, time-consuming to generate, or that may simply be unavailable. Finally, coupling requires compromise between the temporal scales at which component processes occur (Ewert et al., 2011; Voinov and Shugart, 2013) and the scales of interest to stakeholders (Foster and Brozović, 2018; Kelly et al., 2013; Voinov et al., 2016), which are typically longer.

A common approach is to couple independently-developed models in a linear manner that applies one model's output as the next model's input (Belete et al., 2017). Such a sequential approach may overcome complexities related to the cross-scale attributes of the different domains by upscaling the outputs of the first component, once the simulation is completed, to produce the required input for the second component (van Bussel et al., 2016, 2015; Van Ittersum et al., 2013; Van Wart et al., 2013). However, this approach omits feedback dynamics between different components of the integrated model. In contrast, iterative approaches allow the components of the system to exchange intermediate information during runtime, and not just at a single point in time. Where crop models are to be used in an iterative integration approach, the skill of process-based crop models with coarser-than-daily simulation time steps has not been studied and is seldom noted in the literature. We believe this gap results from the absence of process-based models that operate with coarse time steps, and perhaps from a lack of awareness that accurate results are obtainable with longer-than-daily simulation time steps.

An additional consideration is the form of the weather input data used to drive a crop model. The combination of a crop model with coarser temporal resolution weather input data may reduce data collection requirements and yet produce similar model results, and would also allow application of crop models in regions with missing or limited weather input data. The consequently longer simulation time steps may then facilitate incorporation of process-based crop models into integrated assessment models for multidisciplinary studies.

The effects on process-based crop model performance of using longer simulation time steps with temporally aggregated weather input data have not been established, with only a limited number of studies conducted (García-López et al., 2014; Lorite et al., 2005; van Bussel et al., 2011). Further, these studies have a different focus, which is either the temporal aggregation of weather data or the use of empirical approaches for crop production with temporally-aggregated data. The effect of simulation time step length remains essentially unexplored. These observations lead to the two hypotheses of this study: (1) that temporally aggregated input data provide acceptable results for process-based crop models used in integrated assessment studies including policy assessments under future climate, and (2) that longer than daily simulation time steps for crop modeling provide sufficiently accurate results to represent the key functional responses of a crop model – for example, the end of season biomass or yield, or seasonal water requirements – for the same studies. To test the hypotheses, we apply a water-driven, process-based crop growth model to simulate crop biomass and yield accumulations, and total crop water demands, for three crops and regions, using temporally aggregated weather input data and daily, semi-weekly, and weekly simulation time steps. The aims of the study are to provide insight into the applicability of coarser-than-daily simulation time steps to simulate long-term crop yields in integrated assessment models and to investigate the impacts of aggregated weather input data on crop production and water requirements in a process-based crop growth model.

2. Materials and methods

We adapted the water-driven FAO's AquaCrop crop growth model to a system dynamics framework (SD; Forrester, 1961; Sterman, 2000) and revised the calculation routines from AquaCrop's daily time step to a flexible version able to run in daily, semi-weekly, or weekly simulation time step settings (see supporting information in Supplementary Material sections S4 and S5). Called here CropSD, this revised version allows:

1. Testing of the performance of a process-based crop growth model for weekly aggregated weather input data, rather than the typical daily input of AquaCrop, to ensure that the model can accurately reproduce crop biomass and yield and water requirements; and
2. Examination of model performance in simulating crop biomass and yield and water requirements in response to different simulation time steps – specifically daily, semi-weekly, and weekly under a range of water stress scenarios.

Table 1
Soil characteristics for the study locations.

Layer	Texture	Thickness (mm)	Soil water content			K_{sat} (mm d^{-1})
			Saturation (m^3 m^{-3})	Field capacity (m^3 m^{-3})	Wilting point (m^3 m^{-3})	(mm d^{-1})
Enchant, Alberta						
1	Loam	100	0.46	0.31	0.15	250
2	Silt loam	100	0.46	0.33	0.13	250
3	Loam	300	0.47	0.33	0.18	150
4	Clay loam	2000	0.49	0.41	0.22	15
Fincastle, Alberta						
1	Loam	200	0.53	0.29	0.16	250
2	Loam	100	0.47	0.29	0.17	250
3	Silt loam	400	0.47	0.33	0.18	150
4	Silty clay	300	0.49	0.41	0.22	15
5	Silty clay	800	0.49	0.39	0.22	15

Note that our aim is not the development of a new model to replace existing, well-established crop growth models, but instead to test the effects of alternative time steps and temporal aggregation of data on a process-based crop model for integrated assessment purposes.

2.1. AquaCrop: The selection of a process-based model and its growth mechanism

FAO's AquaCrop (v5.0) daily model was chosen because of, 1) the relatively small number of inputs compared to the other models, 2) the availability of documented equations, 3) the use of a water-driven growth engine (Steduto, 2003; Steduto et al., 2012) that is well-suited to conditions where water can be a limiting factor in crop production (van Ittersum et al., 2003), and 4) its popularity for crop modeling applications. AquaCrop has been used to quantify the effects of various water regimes and agronomic and climatic conditions on crop growth and yield (Andarzian et al., 2011; Araya et al., 2010; Evett and Tolk, 2009; García-Vila et al., 2009; García-Vila and Fereres, 2012; Geerts et al., 2010; Hussein et al., 2011; Mkhabela and Bullock, 2012). Its performance has been evaluated, revealing reliable performance and accurate results in simulating crop growth and yield and water requirements both against other well-established models (Abedinpour et al., 2012; Abi Saab et al., 2015; Battisti et al., 2017; Confalonier et al., 2016; Pereira et al., 2015; Todorovic et al., 2009), and against field experiments for various crops (Farahani et al., 2009; Heng et al., 2009; Iqbal et al., 2014; Stricevic et al., 2011; Wellens et al., 2013; Zeleke et al., 2011). More recently, AquaCrop has been reproduced in an open-source (AquaCrop-OS) Matlab (Mathworks Inc, 2015) format to allow parallel execution of the model when large numbers of simulations are needed; see Foster et al. (2017) for details.

AquaCrop separates non-productive soil evaporation from productive crop transpiration, and estimates crop yield by multiplying the biomass by the harvest index (HI) (Raes et al., 2009; Steduto et al., 2012, 2009). It uses thermal time, or growing degree days (GDD), as its default clock and runs with a daily time step. Leaf development in the model is expressed through the canopy ground cover, which is the fraction of soil surface covered by the canopy. The canopy cover is then used as the basis of actual crop transpiration calculations. The model derives the crop biomass from the amount of water transpired (Tr) by the crop using a conservative water productivity parameter (WP*), normalized for atmospheric evaporative demand ET_o and air CO_2 concentration, and is thus applicable to diverse locations and climate conditions, including future climate scenarios (Raes et al., 2006).

2.2. Model scenarios

To address our two hypotheses, a number of test simulations were performed with CropSD to assess the effects of three alternative simulation time steps with weekly weather input data, as compared with daily simulations with daily input data in AquaCrop. These simulations focused on three crops in three different regions – barley in Alberta (two locations), Canada, maize in Nebraska, USA, and potato in Brussels, Belgium. Four irrigation practices and ten growing seasons were selected to reflect a range of climatic conditions and soil moistures at different stages of crop growth, as typical for long temporal-scale applications. Irrigation applications were triggered by the percentage of water depleted from the root zone using four treatments of the total available water (TAW) between field capacity and permanent wilting point for each location: 20% (T20), 40% (T40), 60% (T60), and 100% (T100).

For Alberta, representative barley farms at Enchant (50° 10′ 19″ N, 112° 26′ 11″ W, 811.61 m a.s.l.) and Fincastle (49° 48′ 8″ N, 112° 3′ 45" W, 803.96 m a.s.l.) were simulated over a 10-year period (2006–2015), using the input parameters described below. Barley is grown on about 10% of the total irrigated area of Alberta (AAF, 2017), making it the fourth most-commonly grown irrigated crop in Alberta. Weather input data were obtained from the Alberta Weather Data Viewer of Alberta Agriculture and Forestry (AAF, n.d.). Station records provided daily maximum and minimum temperatures, wind speed measured at 2 m, relative humidity, and solar radiation. The regional climate is characterized as cold semi-arid, with average annual precipitation values for the study period of 333 mm in Enchant and 370 mm in Fincastle. Soil properties were obtained from the Agricultural Region of Alberta Soil Inventory Database (AGRASID, 2013), which contains a collection of soil polygons with all the necessary soil input information. Model data requirements included soil horizon thicknesses; and soil properties, comprising soil water content at saturation (SAT), field capacity (FC), permanent wilting point (PWP), and saturation hydraulic conductivity (K_{sat}). Soil data for the two sites are summarized in Table 1.

Initial soil moisture conditions under all scenarios were set equal to field capacity. Further, because precipitation data were aggregated to a weekly time scale (see Fig. 1 for an example at Enchant of the weekly precipitation and mean temperature inputs compared to their daily counterparts in 2006), Curve Numbers (CN) were not corrected for soil wetness; therefore, one CN value was used that corresponded to Antecedent Moisture Class II (Raes et al., 2012). A CN value of 61 was assumed for all simulations and assigned to the soil configuration of AquaCrop.

Barley input parameters were modified based on AquaCrop's default barley file, which contains both site-specific and conservative (i.e., constant) parameters for the crop. Site-specific parameters were set to local conditions based on Langhorn (2015), who calibrated the various stages of crop phenology, including the growing degree days from seeding to emergence, start of flowering, maximum rooting depth, senescence, and maturity. All crop input parameters used are summarized in Table 2. Similar data were obtained for the other two study locations

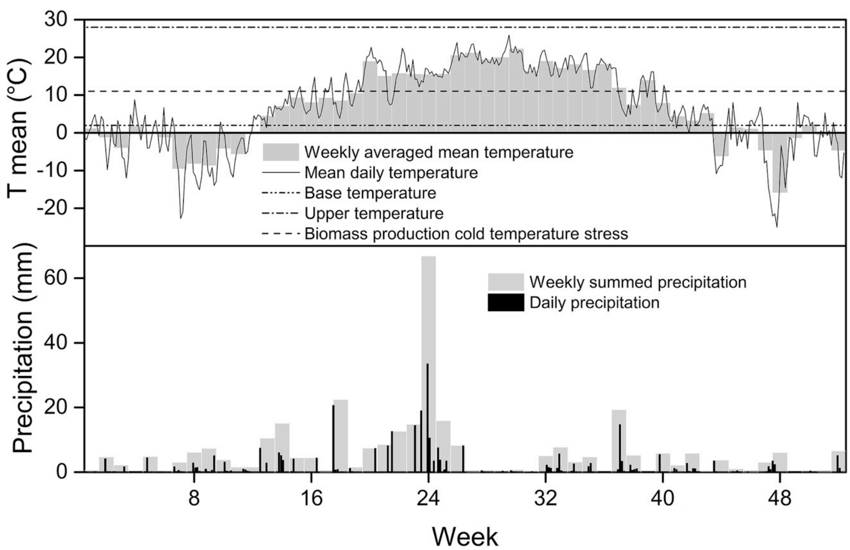

Fig. 1. Sample input to the models: Weekly-averaged mean temperature and precipitation input data for CropSD versus the daily mean temperature and precipitation input data for AquaCrop. Values are shown for 2006, which was chosen arbitrarily as example, for Enchant, Alberta, Canada. Mean temperatures are plotted against threshold base and upper temperatures for barley. Base temperature is the temperature below which crop development does not progress. Upper temperature threshold is the temperature at which the plant no longer develops with an increase in air temperature (Hsiao et al., 2009).

for maize in Nebraska, US and potato in Brussels, Belgium, and are described in sections S2 and S3, respectively, of the Supplementary Material.

2.3. Evaluation criteria

Daily simulation results from AquaCrop based on daily weather input data were used as the reference mode for comparison with results from CropSD for daily, semi-weekly, and weekly time steps with weekly input data. Simulations were compared through statistical measures and graphical results. Using smaller numbers of indicators for assessing model performance can misrepresent average errors and deviations (Chai and Draxler, 2014; Tedeschi, 2006), and thus a combination of metrics was used. The following statistical indices and errors were computed to compare the crop biomass and yield: coefficient of determination (R^2); root mean square error of prediction (RMSE) and its normalized version (NRMSE); mean absolute error (MAE); mean bias error (MBE); and Willmott agreement index (d) (Willmott, 1982). These evaluation procedures have been applied widely to assess crop growth model performance (Abi Saab et al., 2015; Araya et al., 2010; Hsiao et al., 2009; Hussein et al., 2011; Stricevic et al., 2011; Todorovic et al., 2009). Absolute error measures (such as RMSE or MAE) were given

Table 2
Summary of crop parameters for Barley, as adjusted and calibrated to local conditions in southern Alberta.

Parameter	Symbol	Value	Unit	Source[a]
Growth				
Water productivity	WP	15	g m^{-2}	d
Stomatal closure upper threshold	p_{sto}	0.6		d
Shape factor for stomatal closure		3		d
Morphology				
Canopy cover per seedling at 90% emergence	cc_0	1.5		AAF
Number of plants per hectare		3,000,000		AAF
Canopy growth coefficient	CGC	0.008114	% degree-day^{-1}	c
Maximum canopy cover	CC_x	80	%	a
Maximum rooting depth	Z_x	1.3	m	
Shape factor describing root zone expansion		1.5		d
Canopy decline coefficient at senescence	CDC	0.00571	% degree-day^{-1}	c
Crop coefficient for transpiration	$K_{cTR,x}$	1.1		d
Decline of crop coefficient from ageing	f_{age}	1.05	% day^{-1}	d
Upper threshold of water stress for canopy expansion	$p_{exp,upper}$	0.2		d
Lower threshold of water stress for canopy expansion	$p_{exp,lower}$	0.6		d
Shape factor for canopy expansion		3		d
Senescence stress coefficient	p_{sen}	0.55		d
Shape factor for senescence		3		d
Phenology				
GDD from sowing to emergence/recovery		90	degree-day	r
GDD from sowing to maximum rooting depth		756	degree-day	r
GDD from sowing to flowering		810	degree-day	a
GDD from sowing to start of senescence		925	degree-day	r
GDD from sowing to maturity		1350	degree-day	r
Length building up of HI		150	degree-day	a
Base temperature	T_{base}	2	∘C	
Cut-off temperature	T_{upper}	28	∘C	AAF
Harvest				
Reference Harvest Index	HI_0	0.52		a
Reference atmospheric CO_2 concentration (2006)		369.41	ppm	

[a] d: default, AAF: Alberta Agriculture and Forestry (Alberta Agriculture and Forestry (AAF), 2016, 2008, n.d.(AAF), 2016, 2008, n.d.), c: calculated, a: assumed, r: Langhorn (2015).

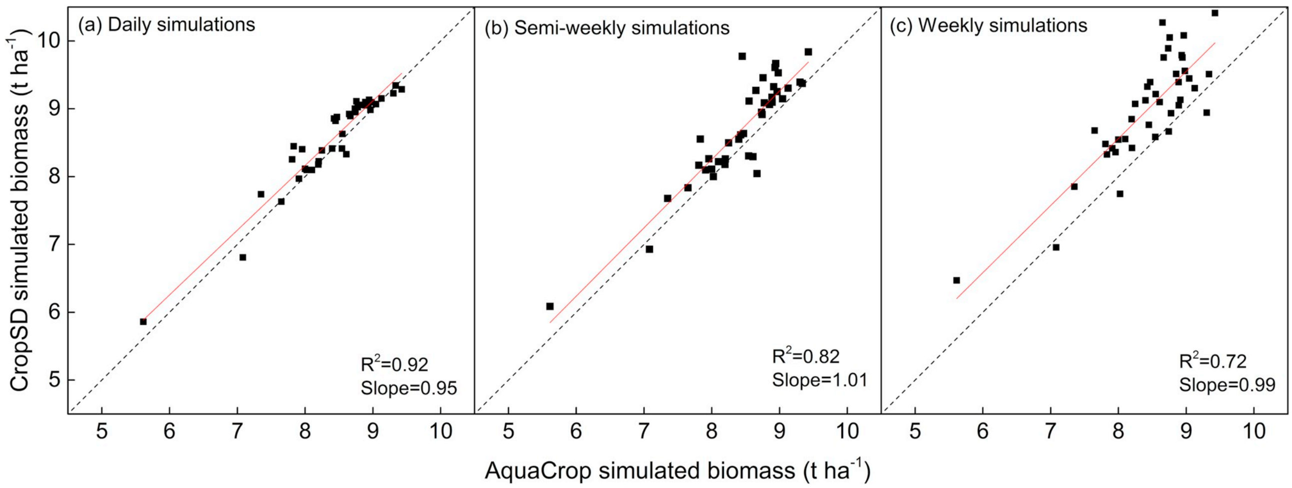

Fig. 2. Aboveground biomass estimated by CropSD versus AquaCrop estimates for barley for the different irrigation treatments over ten growing seasons. The Coefficient of Determination (R^2) and the slope are also shown. Figs. a, b, and c represent the daily, semi-weekly, and weekly simulations respectively for Enchant, Alberta.

more weight for performance assessments, as they provide quantitative estimates of the deviation of the modeled variables from anticipated values, and present the error in the same units as the variable (Bellocchi et al., 2010; Legates and McCabe Jr., 2005; Moriasi et al., 2007).Modeling Efficiency (ME) was also used to evaluate the overall model performance. ME determines the relative magnitude of the residual variance of CropSD compared to the AquaCrop simulation variance. It ranges from $-\infty$ to 1.0, and the closer the result is to unity, the more robust the model is (Nash and Sutcliffe, 1970). Three model variables were also evaluated visually by plotting CropSD and AquaCrop outputs, i.e., soil water content, crop canopy cover, and cumulative actual evapotranspiration. This choice of variables incorporates key aspects of model performance related to the soil water balance, the crop growth mechanism, and the connection of the two components by considering both the actual evaporation from the soil and the actual transpiration by the crop canopy, which sum to the actual evapotranspiration.

3. Results

Daily simulations from the CropSD model with weekly weather data inputs showed high R^2 values for barley biomass and yield simulations as shown in Figs. 2 and 3, respectively, suggesting a high degree of reliability for aggregated weekly input climate data (see results in sections S2 and S3 of the Supplementary Material for maize and potato in the two other study locations). Further, as shown in Fig. 4(a), daily simulations had the lowest NRMSE with a maximum value of 5% for both biomass and yield. Semi-weekly simulations, similarly, showed good statistics with a maximum NRMSE of 7% for biomass and 9% for crop yield, while the weekly time step simulations had the lowest model performance and less agreement with AquaCrop, with a maximum NRMSE of 10%, and R^2 as low as 0.3 for both the biomass and the final yield. Additionally, deviations from the 1:1 straight line for the semi-weekly and weekly simulations were slightly higher than for the daily simulations, and this deviation increased with increasing simulation time steps.

The coarser time step simulations exhibited slight overestimations of both the biomass and the crop yield for the three simulation time steps. For daily simulations, the maximum mean bias error (MBE) was 0.237 t ha^{-1} and 0.135 t ha^{-1} for biomass and yield, respectively, while the maximum MBE for semi-weekly simulations was 0.408 t ha^{-1} for biomass and 0.272 t ha^{-1} for crop yield. The highest MBE was 0.453 t ha^{-1} for biomass and 0.359 t ha^{-1} for crop yield for the weekly simulations.

Fig. 5 provides sample graphical plots that compare daily CropSD and AquaCrop simulation results for soil water content, crop canopy

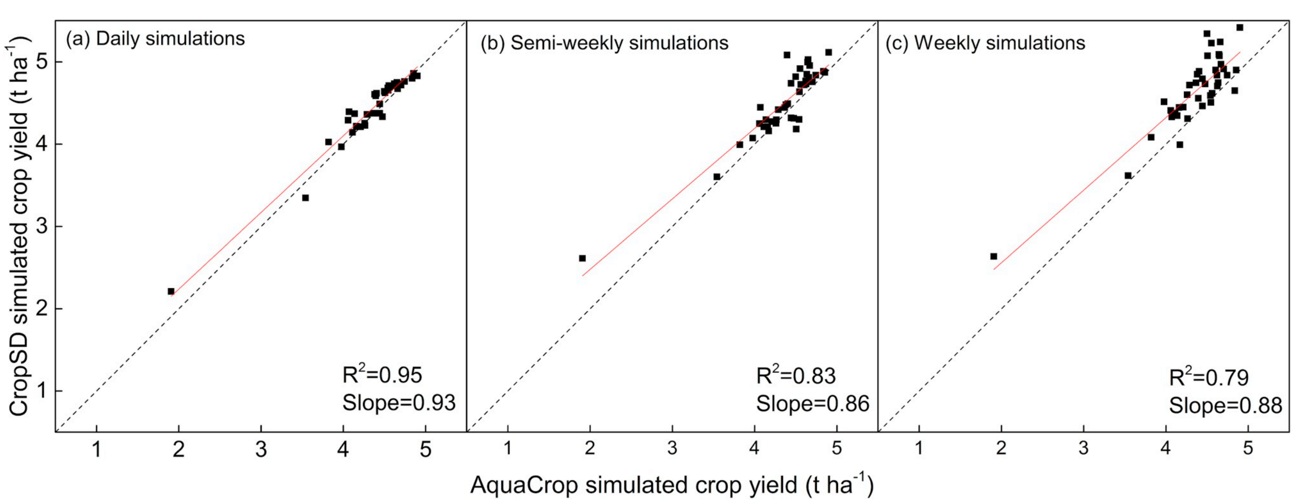

Fig. 3. Crop yields estimated by CropSD versus AquaCrop estimates for barley for the different irrigation treatments over ten growing seasons. The Coefficient of Determination (R^2) and the slope are also shown. Figs. a, b, and c represent the daily, semi-weekly, and weekly simulations respectively for Enchant, Alberta.

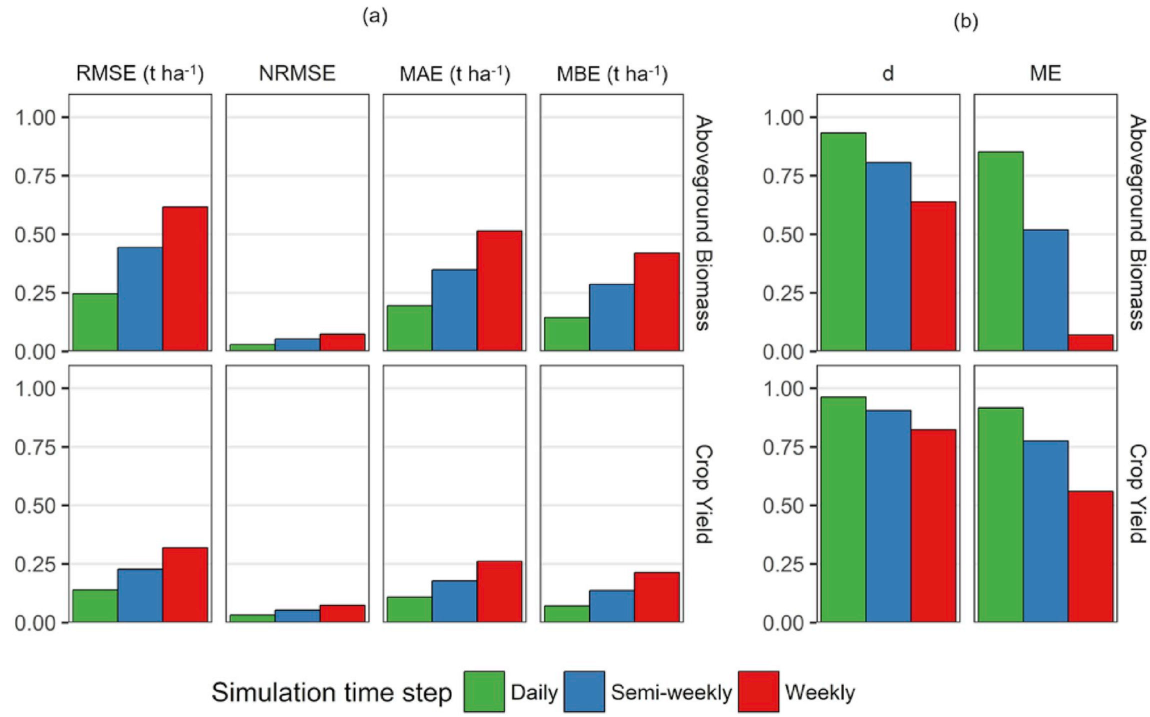

Fig. 4. Crop biomass and crop yield statistics for CropSD versus AquaCrop simulations, based on ten growing seasons and four different irrigation treatments for Enchant, Alberta. (a) Statistics include the root mean square error (RMSE), normalized root mean square error (NRMSE), mean absolute error (MAE), and mean bias error (MBE). Lower values for RMSE, NRMSE, MAE, and MBE indicate better agreement between CropSD and AquaCrop. (b) Statistics include index of agreement (d), and model efficiency (ME). Higher values for d and ME indicate better model performance.

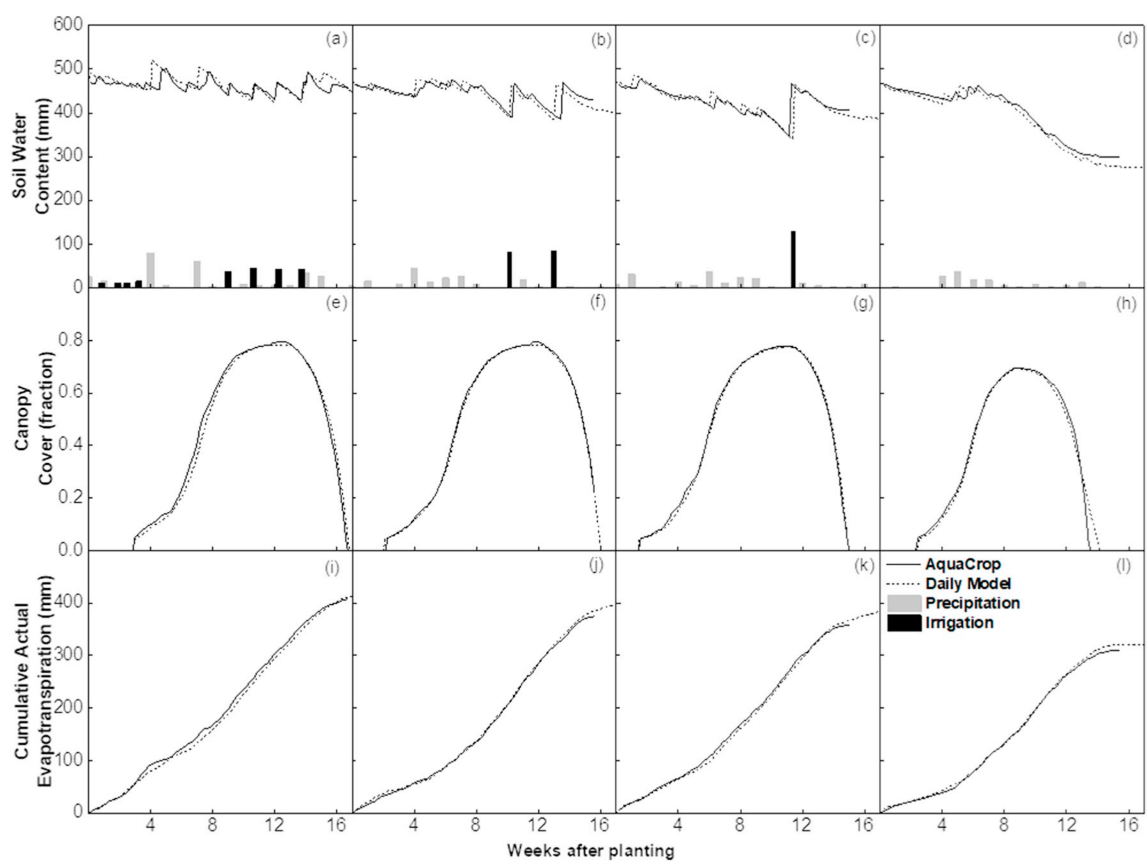

Fig. 5. CropSD daily time step model. Simulated soil water content, crop canopy cover, and cumulative actual evapotranspiration are shown versus simulations from FAO's AquaCrop for the four growing seasons of 2010 (a, e, i), 2011 (b, f, j), 2012 (c, g, k), and 2013 (d, h, l) under four irrigation treatments (T20, T40, T60, and T100) for barley. Precipitation and irrigation events produced by CropSD are also plotted within the soil water content graphs.

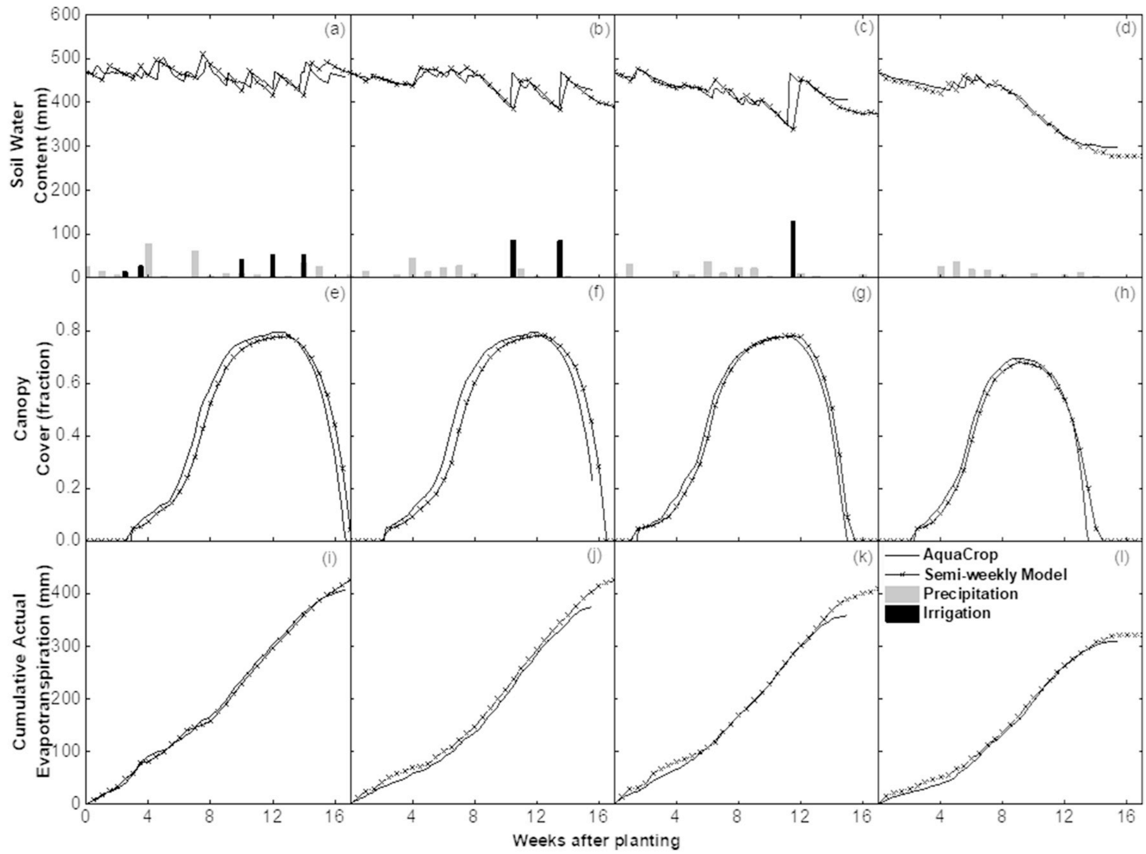

Fig. 6. CropSD semi-weekly time step model. Simulated soil water content, crop canopy cover, and cumulative actual evapotranspiration are shown versus simulations from FAO's AquaCrop for the four growing seasons of 2010 (a, e, i), 2011 (b, f, j), 2012 (c, g, k), and 2013 (d, h, l) under four irrigation treatments (T20, T40, T60, and T100) for barley. Precipitation and irrigation events produced by CropSD are also plotted within the soil water content graphs.

cover, and cumulative actual evapotranspiration variables for the 2010, 2011, 2012, and 2013 growing seasons with the T20, T40, T60, and T100 irrigation treatments respectively at Enchant, Alberta. Similarly, Figs. 6 and 7 compare the semi-weekly and weekly CropSD simulations, respectively. The effect of aggregating daily precipitation into single weekly input values for CropSD is visible in Figs. 5(a) and 6(a) and 7(a) for the daily, semi-weekly, and weekly simulations, respectively, for rainfall events at weeks four and eight after planting. In theory, the aggregation of input data could have two possible consequences for the soil water balance: 1) for dry soils, a single, relatively large weekly precipitation event could produce higher soil moisture as compared with smaller daily precipitation events, or 2) for wet soils in the receiving top layer, greater runoff resulting from larger rainfall events could cause less water infiltration and relatively lower soil moisture. Because no adjustment to the curve number of the topsoil layer of the soil profile was performed, the model behavior corresponded to the first case and tended to calculate slightly higher moisture for the soil profile than crop models driven with daily input, regardless of the time step used.

Longer time steps also affected the simulation of irrigation timing and soil water depletion. Specifically, irrigation applications that fell between two calculation time steps in the semi-weekly and weekly model versions permitted water depletion to exceed the user-set allowable value, because the "trigger to irrigate" (soil water depletion) did not occur until the start of the next calculation step. Therefore, the number of irrigation events was reduced, but the application depths increased to account for the longer delay in applying irrigation, as shown in Table 3. The result was a higher depletion ratio and less available soil moisture for the crop. This effect was particularly apparent at low allowable depletion ratios (as in T20), where small and more frequent irrigation events were required in the AquaCrop and daily time step CropSD models early in the growing season (Fig. 5(a)), because the short roots depleted the required moisture only from the top soil layers and triggered more irrigation events in a short period of time. For example, daily time step simulations resulted in eight irrigation events for T20 (Fig. 5(a)) during the growing season, which agreed with AquaCrop simulations, while five and four irrigation applications for semi-weekly (Fig. 6(a)) and weekly (Fig. 7(a)) time step simulations, respectively, were generated.

CropSD with weekly data inputs simulated the canopy cover (CC) development throughout the growing season identically to AquaCrop under the four irrigation treatments, as presented in Fig. 5(e, f, g, and h). Likewise, the semi-weekly CropSD simulations were almost identical to the CC development from AquaCrop; however, a slight delay in the logistic curve of the canopy growth (Geerts et al., 2009; Steduto et al., 2009) before reaching its maximum value resulted in an overall CC development delay over the growing season – see Fig. 6(e, f, g, and h). This CC development delay increased with increasing simulation time step, as shown by comparing the weekly time step results in Fig. 7(e, f, g, and h) with the daily and semi-weekly simulations. Moreover, weekly simulations occasionally resulted in a larger incremental exponential growth during canopy development. Specifically, the weekly time step CropSD simulations occasionally overshot the growth logistic curve and hence the maximum canopy cover was reached earlier in the season; therefore, the model overestimated transpiration, crop biomass, and crop yield. In other cases, as shown in Fig. 7(h), crop senescence was triggered later in the season, resulting in a larger accumulation of biomass and thus overestimated crop yields. Seasonal actual evapotranspiration (ET) tended to be overestimated regardless of the simulation time step, a result particularly apparent towards the end of the growing season, and likely attributable to the aggregation of the weather input data. Overestimation increased consistently with

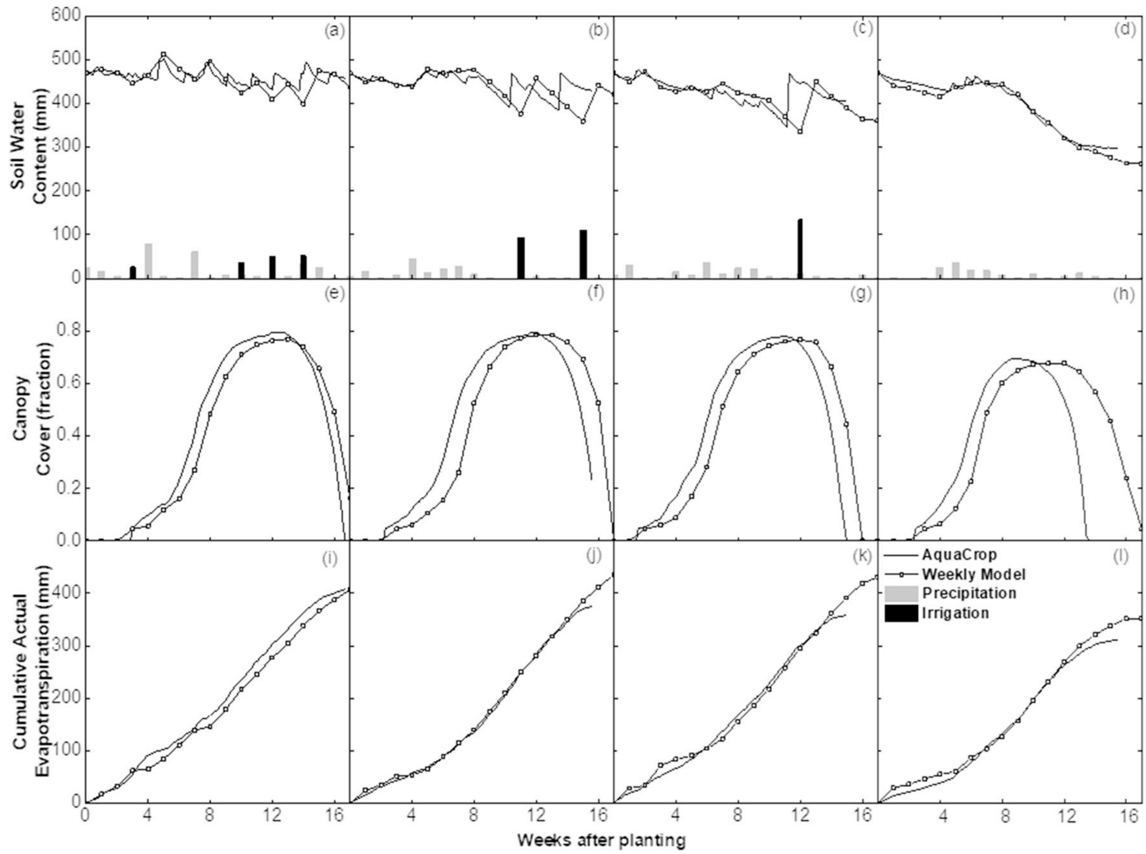

Fig. 7. CropSD weekly time step model. Simulated soil water content, crop canopy cover, and cumulative actual evapotranspiration are shown versus simulations from FAO's AquaCrop for the four growing seasons of 2010 (a, e, i), 2011 (b, f, j), 2012 (c, g, k), and 2013 (d, h, l) under four irrigation treatments (T20, T40, T60, and T100) for barley. Precipitation and irrigation events produced by CropSD are also plotted within the soil water content graphs.

Table 3
Irrigation events characteristics for T20, T40, and T60 for Enchant study location for 2010, 2011, and 2012, respectively.

Model	Number of irrigation events	Minimum irrigation depth (mm)	Maximum irrigation depth (mm)	Seasonal irrigation depth (mm)
		T20		
AquaCrop	8	14	45	238
CropSD				
Daily	8	11	44	228
Semi-weekly	5	14	54	192
Weekly	4	26	55	165
		T40		
AquaCrop	2	84	87	171
CropSD				
Daily	2	81	86	166
Semi-weekly	2	85	86	171
Weekly	2	93	110	202
		T60		
AquaCrop	1	–	–	128
CropSD				
Daily	1	–	–	130
Semi-weekly	1	–	–	130
Weekly	1	–	–	134

increasing simulation time step, as shown by comparing Fig. 5(i, j, k, and l), 6 (i, j, k, and l), and 7 (i, j, k, and l).

Fig. 8 compares all results obtained from CropSD for daily, semi-weekly, and weekly time steps with aggregated weather input data against AquaCrop for biomass and crop yield, respectively. The figures include results for all the irrigation scenarios over ten growing seasons (2006–2015) at both Enchant and Fincastle, Alberta; therefore, each time step-based data set has a total of 80 data points (10 years x 4 treatments x 2 locations) for each of biomass and yield at both locations. The figures show that CropSD reproduced AquaCrop values well for daily and semi-weekly time steps with weekly aggregated climate input data. Specifically, NRMSE values for biomass and crop yield, respectively, were 3% and 5%, and 3% and 6%, for daily and semi-weekly time steps. Results were less promising for the weekly simulations – recall particularly the low ME value for biomass in Fig. 4, indicating that the weekly time step model may not be used with confidence. Further, deviations for lower biomass and crop yield estimates (values closer to the origin) were found to be higher than for high-yielding conditions. These deviations also increased with increasing simulation time step length.

4. Discussion

4.1. Implications of simulation time steps for crop biomass and yield estimates

When both models were run at a daily time step, biomass production and crop yield in AquaCrop and CropSD differed slightly for two reasons. First, climate data for CropSD were input as weekly averages for the temperature, relative humidity, and wind speed, and the total weekly precipitation was applied at the beginning of the week. Second, CropSD operates with a base time unit of one week, and uses the Euler method to solve the differential equations numerically, which changes time steps according to a geometric progression with a common ratio of one-half (Lehn et al., 2002); therefore, the model ran at a time step of one-eighth of a week rather than one-seventh, introducing a slight discrepancy in values.

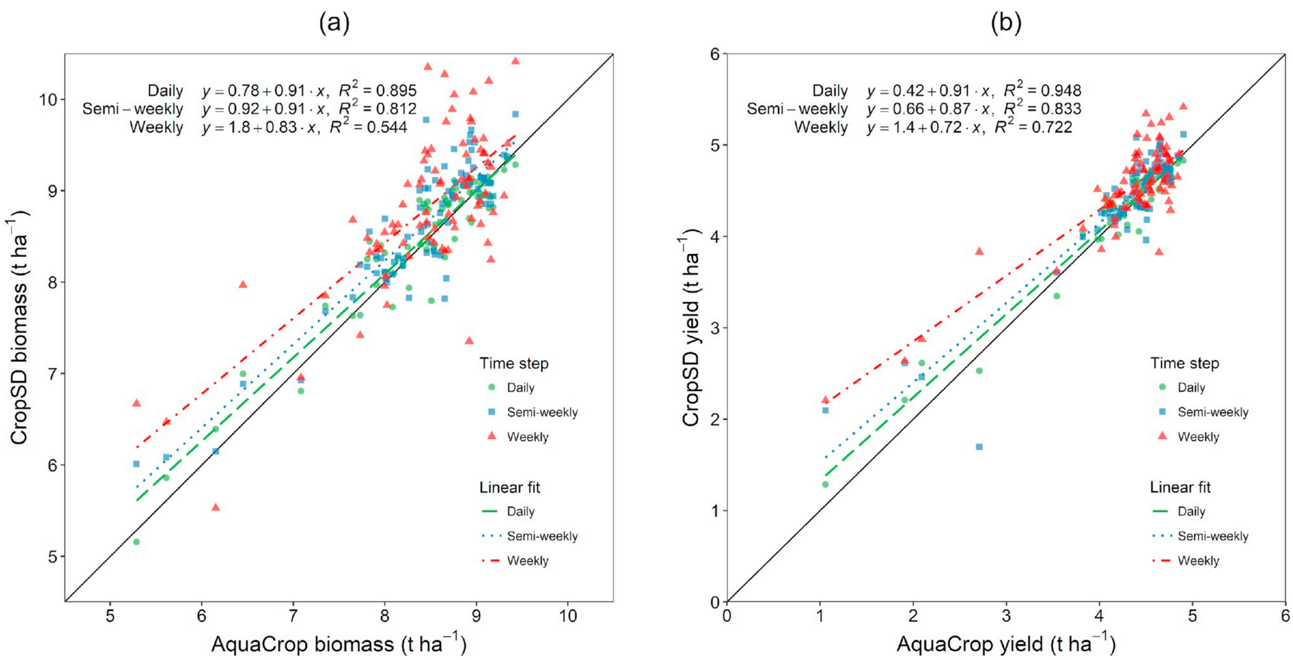

Fig. 8. Daily, semi-weekly, and weekly time step results for CropSD versus AquaCrop in simulating (a) aboveground biomass and (b) crop yield for the two study locations of Enchant and Fincastle. Each of the three datasets has 80 estimated data points derived from simulating two locations for barley crop over ten growing seasons using four irrigation treatments.

In the coarser semi-weekly and weekly time step simulations, delayed canopy growth in the early stages of crop development resulted, in most cases, in a lag period of up to half a week for the semi-weekly simulation and up to a week in the weekly time step simulation. The fact that this effect was more pronounced with longer simulation time steps adds uncertainty to the use of weekly time steps. The delay may occur for one or both of the following reasons: (i) higher soil water depletion was permitted than the specified irrigation threshold because of the coarser time step, since the irrigation threshold was reached between two computation steps, or (ii) computational errors occurred that were associated with the Euler integration method. Integration error is proportional to the square of the time step; therefore, coarser integration step-sizes correspond to larger errors. The first reason was more evident in weekly simulations, where irrigation was simulated as taking place later in the season – see Fig. 7(a, b, and c). Although weekly simulations come closer to the longer simulation time steps of integrated models, the results are not promising for biomass or crop yield estimations where high accuracy is the aim. Weekly time step results consistently showed large deviations from AquaCrop results in terms of soil water moisture, canopy cover, and seasonal ET, because of changes in simulated variables that occurred too quickly for the weekly time step to capture accurately.

4.2. Implications of simulation time steps for soil water moisture, canopy cover, and seasonal evapotranspiration

Soil layers in CropSD tended to retain moisture above field capacity longer than AquaCrop, because of a modification in the calculation of infiltration processes at longer time steps. The effect was particularly evident for larger precipitation events (which were aggregated to weekly input values) with semi-weekly and weekly time steps. These results were comparable to those of Lorite et al. (2005), who showed that longer simulation time steps do not accurately capture infiltration and runoff and thus the soil water content, especially for heavy rain events or for periods of continuous rain. In most cases, the coarse simulation time steps were longer than the time to infiltrate from one layer to another in coarse soil textures with higher hydraulic conductivities. Therefore, the drainage and distribution component of the model was modified (see Table S2) for both the semi-weekly and weekly simulation settings, so that CropSD bypassed the drainage and redistribution calculations and modeled any water above field capacity in the soil layers as draining instantly after a heavy rain or irrigation event. This approach maintained field capacity as the maximum soil water content to approximate the final state (post soil-water redistribution) of the soil moisture after a wetting event. Meng and Quiring (2008) showed that simulating soil water content at a monthly scale captured annual cycles and interannual variability of soil moisture, but that it could not simulate the actual soil moisture. Baker et al. (2010) also showed overestimation of the available soil water content in a forest growth model (3 PG+) using a monthly simulation time step. However, in their comparison of the daily and monthly simulations, single- and multiple-layer soil models were employed respectively; therefore, the finding can be attributed to both the simulation time step and to the model structure, as the single-layer model treated the soil profile as a single, homogeneous unit.

The canopy is a central component of the model because it drives the actual transpiration, which in turn determines the biomass production and thus the crop yield (Raes et al., 2009; Steduto et al., 2009). AquaCrop simulates canopy cover development in terms of GDD increments, starting from transplanting or sowing to the final harvest. A coarser simulation time step causes larger incremental increases in GDD accumulation. In some cases, the GDD accumulation over one time step (particularly for the weekly time step) was large enough for the exponential growth component of the logistic curve to overshoot and thus exceed the maximum canopy cover; where this occurred, the model bypassed the decay component of the logistic curve. Consequently, the canopy cover was represented unrealistically, as seen in Fig. 7(h), where the development curve was composed only of exponential growth and was then capped at the maximum crop canopy cover. In general, the simulation time step should be smaller than the shortest period over which a change in a model variable is likely to occur. Otherwise, the model behavior may differ significantly from what would occur with a smaller time step, as demonstrated by the soil water content in Fig. 7(a, b, and c).

Systematic overestimation was observed for the seasonal ET in CropSD, as compared with AquaCrop. This overestimation, and its

increasing magnitude with coarser time steps, was attributed to the delayed canopy development by the model. The delay resulted in larger transpiration rates towards the end of the season, where the canopy cover senescence was triggered later in the season than in reality, such that more transpiration took place and increased the seasonal ET. Similarly, Sall et al. (2017) quantified differences between daily and hourly reference ET computation and also showed that longer time steps resulted in overestimation. For their forest growth model (3 PG+), Baker et al. (2010) showed that monthly simulations led to a fixed proportion of rainfall intercepted by the canopy and an underestimation of transpiration.

4.3. Implications of temporally-aggregated weather input data for model performance

Lack of day-to-day variability in maximum and minimum temperatures – and the corresponding absence of extreme temperatures – resulted in higher estimated aboveground biomass and crop yields, particularly in regions/conditions of high temperature variability. These results match expectations and confirm earlier work on temporal weather data aggregation (Nonhebel, 1994; Soltani et al., 2004). Specifically, in our study locations, both cold and heat stresses were reduced or eliminated by the weekly averaging of CropSD input (recall Fig. 1, above); therefore, overestimations in biomass production and crop yield are more likely caused by these omitted stresses than by differences in the accumulated thermal heat units. Similarly, using interpolated daily temperature and radiation data, van Bussel et al. (2011) found an overestimation of simulated biomass driven by a lack of weather variability and higher photosynthetic rates; without weather variability, average temperatures were more often at or near optimal values for growth. Heat stresses are known to affect crop production strongly (Hatfield and Prueger, 2015), and their damaging effects can occur after exposure to high temperatures of only three days for barley (Savin and Nicolas, 1996), and only one day for wheat (Saini and Aspinall, 1982). Likewise, cold stresses decrease root hydraulic conductance, reducing root growth and ultimately decreasing crop production (Thakur et al., 2010) after exposure to low temperatures for as little as one day (Ercoli et al., 2004). Overall, the level of detail in a process-based crop model affects its response to temporal data aggregation (Adam et al., 2011; van Bussel et al., 2011).

Finally, Lorite et al. (2005) considered the effects of temporal aggregation on irrigation requirements using the statistical crop production function of Doorenbos and Kassam (1979), and showed little effect of temporal aggregation on seasonal irrigation requirements up to monthly time steps. However, while Lorite et al. (2005) found decreased irrigation requirements with larger time steps, our analysis showed that longer simulation time steps caused both the number of irrigation events and the seasonal-total irrigation depth to decrease only for low allowable depletion ratios (T20) – see Table 3. This is due to irrigation events occurring at a shorter interval than the simulation time step. In contrast, the total number of irrigation events and seasonal irrigation depth for both T40 and T60 were comparable to those simulated by AquaCrop, because the intervals between irrigation events were longer than half a week to a full week, and thus the model was able to accurately capture the events.

4.4. Caveats of the study

The results of this analysis are influenced by the features of AquaCrop model and its water-driven mechanism. To generalize the hypothesis that coarser simulation time steps for process-based crop models are suitable for incorporation into integrated assessments, investigation of the characteristics of other crop growth mechanisms (radiation- and carbon-driven) is necessary. Further, given the results for the weekly time step simulations, AquaCrop may be more detailed than necessary for weekly simulations, and so functional approaches with summarized processes may prove worthwhile.

5. Conclusions

For policy planning under climate change, integrating agricultural models into broader socioeconomic or environmental applications requires the accurate simulation of agricultural production through process-based crop models. We hypothesized that process-based crop models can operate accurately under coarser-than-daily simulations and with aggregated weather input data, and argued that such an approach would provide a useful compromise between accuracy, model inputs, and simulation time step suitability for model integration.

The hypotheses were tested with a revised version of a water-driven crop model, AquaCrop, designed to operate with a coarser time step and weekly input data. This model, called CropSD, then provided insights into the performance of a process-based crop model in simulating crop yield and water requirements. We found that temporal aggregation of weather data resulted in a slight overestimation of both the biomass and yield. Longer time steps amplified the impacts of weather input data aggregation, and overestimation became more pronounced with increases in the simulation time step. Both daily and semi-weekly time steps simulations agreed closely for crop growth and production, and soil moisture simulations. As compared with the AquaCrop results, weekly time step CropSD simulations consistently showed the highest deviations and the lowest performance for all model variables: crop biomass and yield, soil water moisture, canopy cover, and seasonal ET.

Our results showed that 1) water-driven process-based approaches to crop modeling can operate accurately at coarser simulation time steps than daily, and 2) a semi-weekly time step may provide a promising alternative in conjunction with coarser (up to weekly) temporal resolution weather input data. These findings have important implications for coupling crop models with other social, economic, or environmental models in integrated assessment studies for purposes such as policy assessment, evaluation of food security, and resource use and efficiency under future climate conditions. Despite the growing literature and interest in broadening process-based crop model applications, there still appears to be little work in improving process-based crop models for use in integrated assessment and modeling. This paper is intended as a step in that direction.

Additional information

Declarations of interest: none.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.03.030.

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